A SIMPLE GRAPHICAL TECHNIQUE FOR CONDITIONAL LONG RANGE FORECASTING OF BELOW-AVERAGE RAINFALL PERIODS IN THE TUVALU ISLANDS, WESTERN PACIFIC

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Abstract

For the Tuvalu Island group in the western Pacific, a simple graphical method is proposed as a means of forecasting whether rainfall totals for the next 1, 2 ...6 months will be below average. The method is based on scatter plots where the points are color-coded as above- or below average rainfall, with the plot axes being lag-1 and lag-2 NINO4 sea surface temperatures. Within the scatter plots there are reasonably clear data fields with higher frequencies of below-average rainfalls associated with cooler precursor NINO4 temperatures. These data fields are defined by subjectively-emplaced separation lines which bifurcate the scatter plots into "predictable" and "unpredictable" fields. If two precursor NINO4 temperature values define a point located in a predictable field then a warning would be issued for below-average rainfall over the next n-month period, depending on the time scale of the scatter plot. A long rainfall record at Funafuti in Tuvalu indicates that success in predictable-field forecasting of below-average rainfalls would range between 68% for 1-month rainfall totals and 89% for 6-month totals. The forecasting success derives from persistence of cooler NINO4 sea surface temperatures which are associated with lower rainfalls in Tuvalu. However, many dry periods are also located in the unpredictable field and cannot be forecast by this method.

INTRODUCTION

The scattered low-lying atolls of the small island nation of Tuvalu are located in the region 5^{o}S to 11^{o}S and 176^{o}E to 180^{o}E in the western Pacific Ocean (Fig. 1). The islands' climate reflects the alternating influences of the Intertropical Convergence Zone and the South Pacific Convergence Zone (Thompson, 1987; Wyrtki and Meyers, 1976). This gives rise to annual precipitation variation with a dry season from April through November and a wet season from December through March (Fig. 2). Easterly trade winds prevail except in the wet season when winds blow from the west or north.

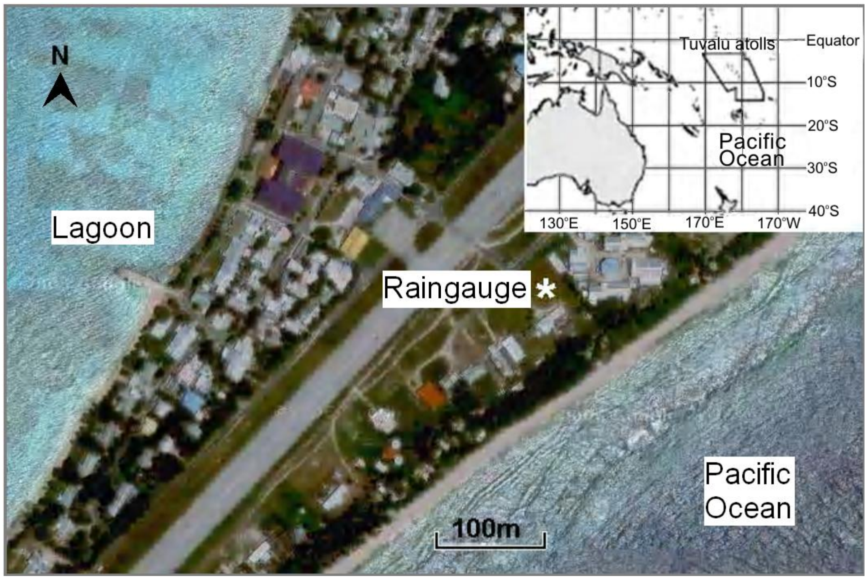

Figure 1. Tuvalu Islands location and rain gauge site on Funafuti Atoll, Tuvalu.

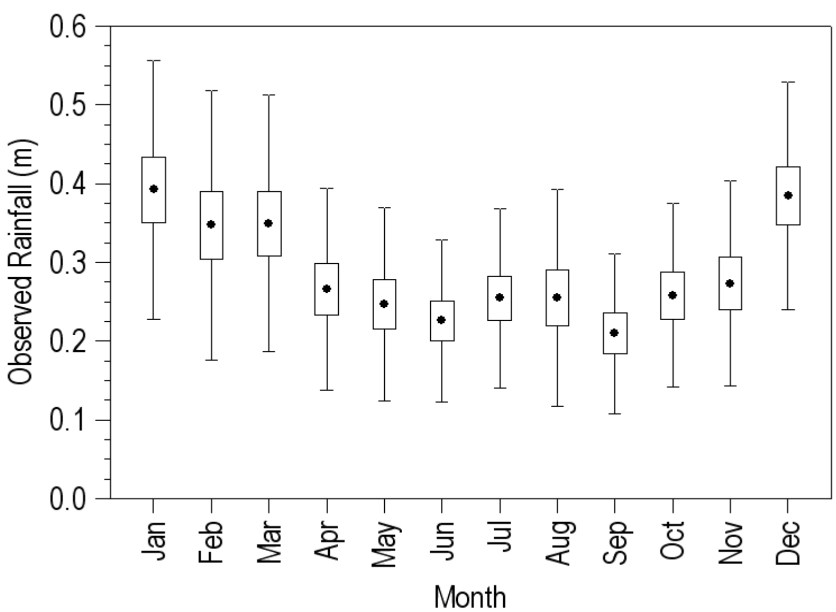

Figure 2. Mean monthly rainfall at Funafuti, Tuvalu. Solid points denote means, boxes are ±2 standard errors, and line range is ±1 standard deviation.

The Tuvalu atolls experience extended droughts which have a significant social impact because rain is the only source of fresh water to the local population. Developing some ability to forecast future below-average rainfall periods is seen as advantageous to encourage early conservation of tank water supplies. The Southern Oscillation Index (SOI) has provided some basis for attempting rainfall forecasting in Tuvalu (Thompson, 1987). However, we found that sea surface temperatures in the NINO4 region[1] were the most useful for anticipating dry periods. We report here a simple graphical forecasting approach which uses precursor NINO4 temperatures for the specific aim of forecasting extended periods of below-average rainfall in Tuvalu. Other more sophisticated methods are in current use eg SCOPIC (http://www.bom.gov.au/climate/pi-cpp/scopic.shtml) but the non-statistical graphical approach here, while not necessarily more accurate, has the advantage of ease of understanding and visualisation for the general population.

FORECASTING TECHNIQUE

Model-based forecasting methods have been used for anticipating long-range precipitation characteristics in various localities. For example, a neural network model was used to forecast droughts in the Kansabati River Basin in West Bengal in India (Misra and Desai, 2006) and logistic regression models were used to forecast above or below-average winter precipitation in the southern and central United States (Kurtzman and Scanlon, 2007). However, we found that both linear regression and neural networks were unable to anticipate Tuvalu dry periods from a range of independent variables which included lagged values of the SOI, sea surface temperatures, and previous mean rainfalls. In seeking an alternative approach, we inspected a large number of scatter plots of Tuvalu rainfall against the various independent variables. The NINO4 plots in particular indicated that they could be employed in a simple graphical approach to anticipate many dry periods. This method was investigated with respect to the long rain gauge record (1945-2007) from Funafuti Atoll, the main population centre of Tuvalu (Fig. 2).

The derivation of the method is illustrated here for the 1-month time scale where the aim is to forecast whether the coming month will have below-average rainfall. The monthly rainfall totals were first expressed as positive or negative deviations from their respective long-term means as obtained from the entire record. Next, a

[1] http://gcmd.nasa.gov/records/GCMD_NOAA_NWS_CPC_NINO4.html

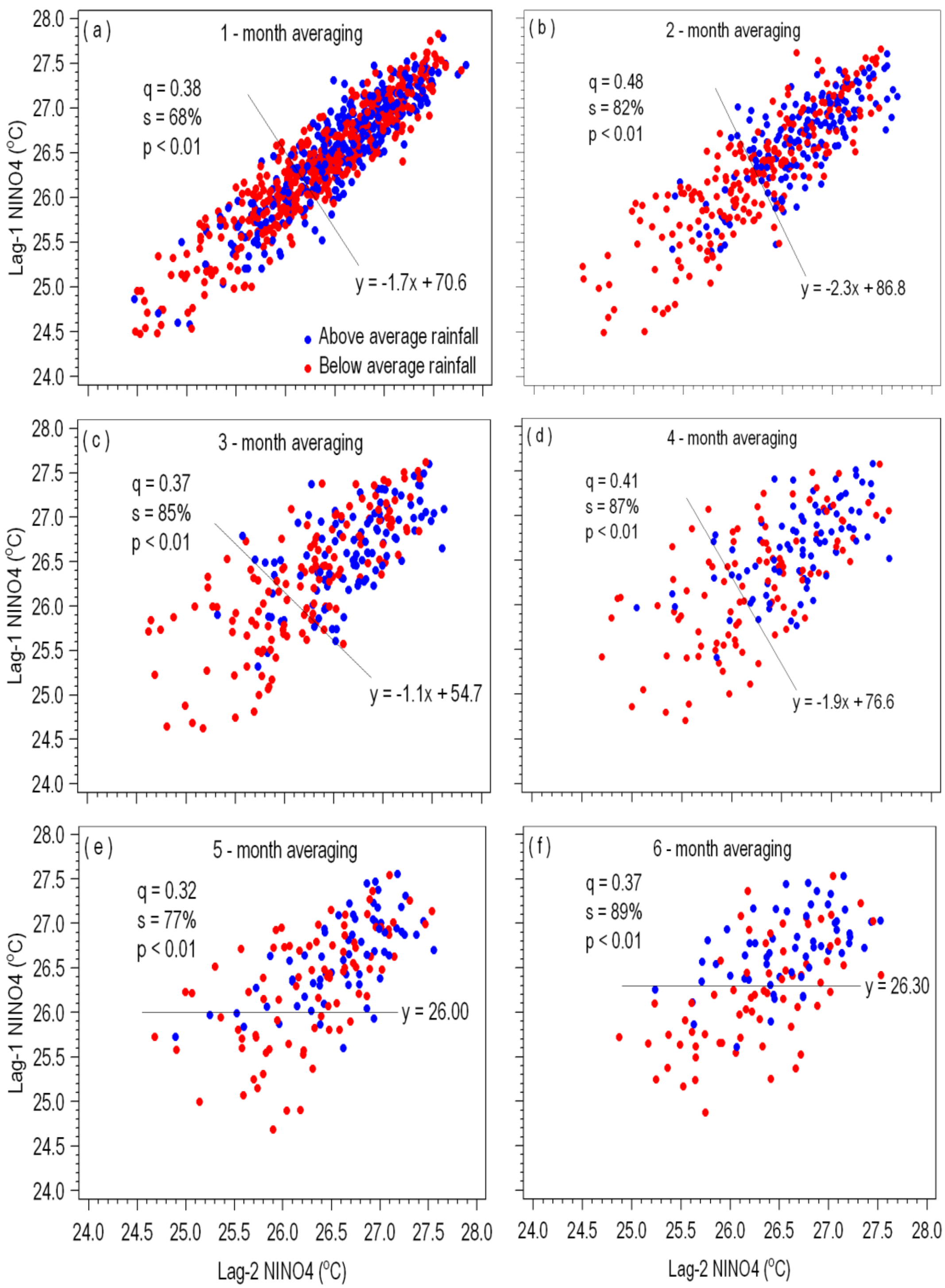

Figure 3 (a-f). Scatter plots showing above or below average rainfall at Funafuti as a function of lag-1 (y axis) and lag-2 (x axis) NINO4 sea surface temperature values for various averaging times. The "predictable" subset of below-average rainfall is defined as the field below the emplaced partition line (equation shown). See text for further description.

NINO4 time series was constructed as monthly mean temperature values derived from averaging daily NINO4 values. The monthly rainfall deviations are shown in Fig. 3a as a two-color scatter plot of blue (positive) and red (negative) points, with each point's *y* and *x* coordinates being NINO4 monthly temperature averages lagged by 1 and 2 months, respectively.

There is evidently a zone of color clustering in Fig. 3 with a greater proportion of red points when both lag-1 and lag-2 NINO4 values plot in the lower portion of their ranges. This zonation allows emplacement of a subjective linear partition which bifurcates the data scatter and defines a predominantly red zone in the lower portion of the scatter plot.

For example, the value of *s* = 68% in Fig.3a gives the percentage of below-average rainfall months (red points) relative to all the points in the data field below the partition. In a forecasting context, this means that if the lag-1 and lag-2 values of NINO4 plot below the linear partition then a warning of below-average rainfall for the month ahead will be correct with probability 0.68.

The *p* value denotes the significance level of *s*, obtained from a randomization procedure. This comprises repeated random placement of the colored points over the original point locations, with *p* being the proportion of times the original *s* value is exceeded. The value *q* denotes the proportion of all months on record which fall below the partition line. That is, low rainfall warnings can be issued for the coming month for 38% of the time only, but the warnings when given have an 0.68 probability of being correct.

A limitation of the method is evident in that despite the high conditional success rate, below-average rainfall months plotting above the partition line cannot be forecast. There is a trade-off here in the subjective choice of location of the partitioning line. Locating the lines at lower positions give a higher value of *s* at the expense of a low value of *q,* which would mean that below-average rainfall forecasts could only be made rarely.

The same approach can be applied to longer averaging times to make forecasts of above or below average Funafuti rainfall totals for coming 2,3,…6 month periods (Fig.3b-f). That is, both the rainfalls and lag NINO4 values have a common *n*-month time scale and the temperatures are averaged over the *n*-month period concerned. For averaging times longer than four months the lag-2 value of NINO4 appears too far back in time to contribute to forecasting accuracy. The linear partition is then simply a subjective horizontal line corresponding to a specific lag-1 NINO4 temperature value. However, the scatter plot format is maintained for consistency in these cases (Fig.3e, f). The conditional forecast accuracies are surprisingly high over the various averaging times, reaching a maximum of 89% when forecasting below-average rainfall for the next 6-month period.

A below-average rainfall forecast for a given *n*-month period need not imply that all months within that period will be drier. However, there does appear to be a bias toward individual months' rainfalls in these instances being less than their respective long-term averages (Fig. 4).

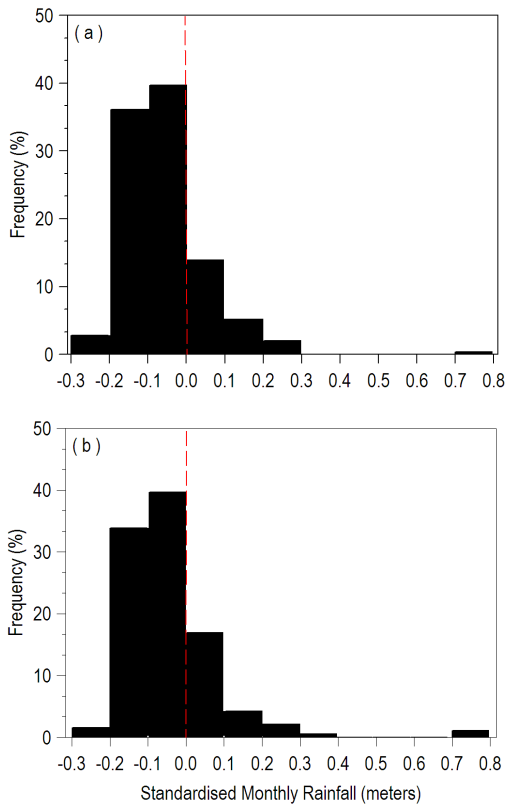

Figure 4 (a,b). Histograms of percent frequency distributions of individual monthly rainfalls from within all 2-month and 3-month periods forecast to have below-average rainfall.

The thermal inertia effect of sea surface temperatures creates serial correlation between the lag-1 and lag-2 NINO4 temperatures for smaller averaging times (Fig. 3). This correlation does not contribute directly to forecasting but an implication here is that there is serial correlation of correct forecasts which means the randomization test is compromised to some degree because serial correlation in the original data will give rise to low *p* values when random reordering is applied. It is nonetheless encouraging that low *p* values are maintained when the NINO4 serial correlations decrease with longer averaging times.

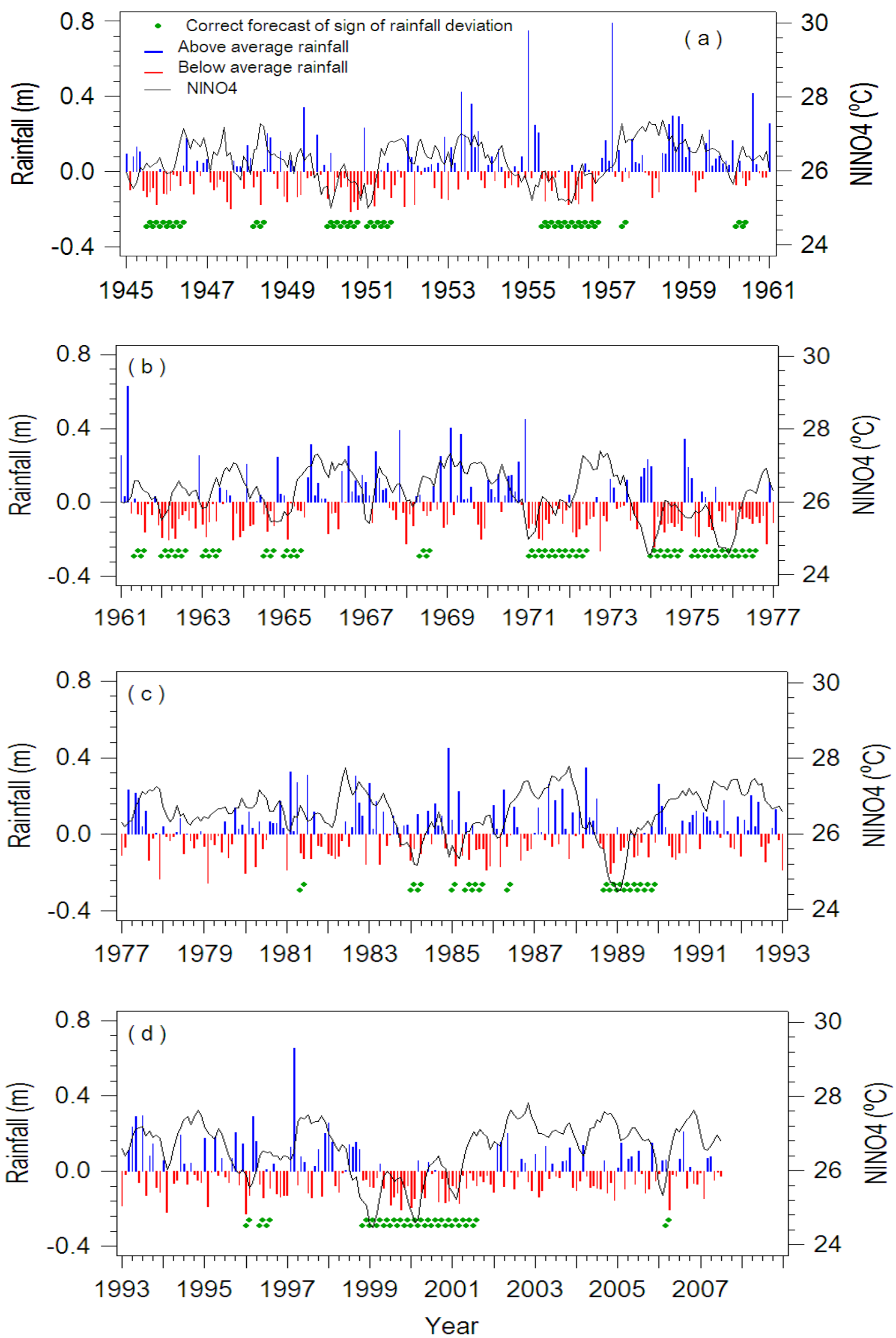

Figure 5 (a-d). Monthly time series (1945-2007) of NINO4 sea surface temperatures and Funafuti rainfall deviations from respective long-term monthly means. Green points denote times of correct forecasts of 2-month periods having less than average rainfall, plotted in two rows to avoid overlap.

The success of the conditional forecasting method derives mostly from persistence of cooler NINO4 ocean temperatures, which tend to be associated with lower rainfalls at Funafuti. This is illustrated in Fig. 5 for the 2-month time scale where there is strong clustering of correct forecasts of below-average rainfalls. Persistence of cooler ocean temperatures at the 1-month time scale is illustrated by the runs histogram in Fig.6, where 70% of NINO4 runs below 26 ºC are of at least three months in duration.

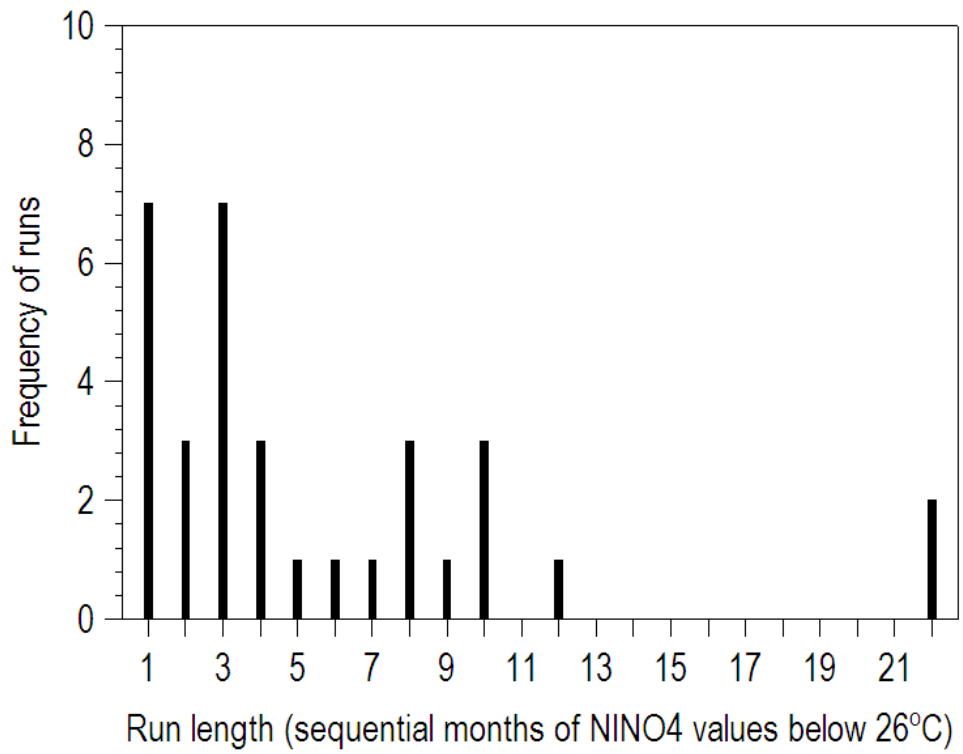

Figure 6. Frequency histogram of run durations of sequential months of NINO4 sea surface temperatures below 26°C, (1945-2007).

DISCUSSION

The forecasting method presented here was developed with reference to hindcasts rather than actual forecasts as such, so true validation will be determined by future application. However, the simplicity of the method and its success in hindcast data application give some confidence that the method will be useful for practical forecasting applications in the future.

We evaluated the graphical approach with other combinations of potential predictor variables also, including lagged values of SOI. However, we did not find any rainfall predictability fields as well defined as for NINO4. This is presumably due to the dominating effect of the proximity of the NINO4 temperature region to the north of Tuvalu.

Our earlier lack of success of regression and neural networks appears to have been a consequence of inconsistent causality in the independent variables. That is, for higher NINO4 temperatures there is a breakdown in the correlation between the sign of rainfall deviations and the precursor ocean temperatures. Even within the prediction subset we were unable to establish any quantitative linkage between the magnitude of the NINO4 lower temperatures and the magnitude of negative rainfall deviations. More sophisticated approaches to modeling might incorporate Markov chain models with “predictability” and “unpredictability” as two possible states of the system.

While the forecasting approach adopted is empirical, we recognize that Tuvalau below-average rainfalls are caused by various physical oceanographic factors such as association of precipitation with migration of atmospheric convergence zones, the current strength of the Southern Oscillation, and ocean heat content (Flohn, 1967; Wyrtki and Meyers, 1976; Alory and Delcroix, 1999; Thompson, 1987; Ueyama and Deser, 2008; Amador and others, 2006; Folland and others, 2002, Basher and Zheng, 1998; Ruiz and others, 2006). Further developments in forecasting Tuvalu dry periods might therefore derive from global climate models. However, the graphical approach given here has the advantage of being visual and easily understandable to the local population, as well as giving a visual indication of forecast error. It would be useful to check whether the method might also be extended to other island nations in the Equatorial Pacific, with reference to lagged values of their respective local ocean temperatures.

CONCLUSION AND FURTHER STUDY

Cooler ocean temperatures in the NINO4 region are associated with below-average rainfall in Tuvalu. Persistence of these cooler temperatures allows quite accurate forecasting of less than average rainfall using a simple graphical technique, although the rainfall magnitude cannot be forecast. The ability to make a forecast of below-average rainfall is conditional on cooler precursor NINO4 ocean temperatures and those dry periods associated with warmer ocean temperatures cannot be predicted.

Further work might focus on the warm-ocean dry periods to forecast a higher proportion of dry periods at Tuvalu. In this regard it might prove possible to move the forecasting threshold away from the simple long-term average and identify instead a higher threshold value between two populations of greater and lesser rainfall. A breakdown of forecast accuracy via season could also be investigated because below-average rainfall in the drier portion of the year is likely to have more social impact.

It would be interesting to compare the accuracy of the graphical method with the more sophisticated methods such as SCOPIC, perhaps leading to blending the graphical and statistical approaches in some way so that the inherent simplicity and visualisation of the graphical method is preserved. A hybrid model of this nature might be of value in forecasting shorter time periods than the monthly units considered here.

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